The Logic Band©: A Novel Neural Network Design For Advancing Artificial Intelligence.

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*Abstract*—The Logic Band is a novel architecture that was inspired by combining neuroscience knowledge with data science. The resulting enhancement, that is designed to fit into any neural network, improves model performance by enabling the artificial intelligence to locate and evaluate complex feature relationships. The enhanced architecture is designed in a way produces exceptional improvement without significant computational resource cost. The following describes the theology and functionality in detail, while offering a new avenue of growth in the advancement of Artificial Intelligence. The conception of the idea through to proof of concept and architecture design throughout various neural networks.

Keywords—Artificial Intelligence, Neural Network, Logic Band, Data Science, Machine Learning, Deep Learning, Novel Advancement.

# **Neuroscience meets Data Science**

The goal of artificial intelligence (AI) is to mimic, as closely as possible, human intelligence. The evolution of technology has made leaps and bounds in humanity’s attempts to artificially simulate intelligence. The weighted simulated connections of an artificial neural network do not perfectly represent the natural synapsis of neurons within the human brain. To create artificial intelligence, you first must know how natural intelligence truly exists and works… yet this is something that is not fully understood in the scientific community. The scientific community understands that neurons transmit information across the brain. Three different types of neurons serve different functions within the brain. Even with all we know about neuroscience, there is still so much that we only have theorized about the human brain.

The human brain contains countless amounts of neurons and various types, which include unipolar, bipolar, multipolar, and pseudounipolar each with their own specific structure and function. Though, the belief is there are hundreds of different types of neurons, it is agreed they make up three categories which are sensory, motor, and interneurons. Sensory neurons carry information between sensory organs and the brain. They take in all the information from the outside world and deliver it to be processed by our brain. Motor neurons carry signals from our brain out to different parts of our body controlling voluntary muscle groups. In short, they take what our brain wants done and deliver it to the part of the body that will fulfill that order. Finally, some interneurons make up the pathways that connect these two together. Like how the nucleus of a neuron directs traffic and maintains order, the interneurons do the same for the sensory and motor neurons.

The human brain is an amazing wonder, and to be able to truly mimic it, one would have to answer many of today’s leading neuroscience’s unanswered questions. However, today we have developed a weighted transport system to attempt to create an artificial replica of the neural synapse that occurs within all of us. This system is designed to take combinations of inputs and train a model to develop an artificial logic to determine the importance of the features provided in producing a desired outcome. These weights are placed on the connections as the model trains and determine the importance of each feature. This is the best substitute available to supply an artificial intelligence with logic and a decisive thought process. This process, yet adequate, does not truly fulfill the goal of artificial intelligence, which is to be as close to a replica of human intelligence as possible.

The current artificial neural networks are built based on neurons and the transmission of data from input nodes through each neural network's unique architecture, to an eventual output node. Each individual network’s design is to establish weights assigned to features to help determine each feature's importance in determining an accurate or correct outcome. These weights are evaluated and adjusted through backpropagation and other means, depending on the type of neural network being used. The accuracy of these neural networks can be fine-tuned through a multitude of different Machine Learning Techniques. The current artificial neural networks are very highly sophisticated representations of gray matter and complex layers of neurons that perform various miraculous computational feats.

# **Artificial Intelligences’ Missing Brain**

Unfortunately, at the end of the day there is no replacement or replication of human thought and logic. I believe that there is a way we can get closer simply by looking a little deeper into the human processes of the mind, into human thought and consciousness itself. Now, I am not proposing a sentient AI in any form. However, we have been building artificial neural networks simply on the information and impulse transportation system of the brain. The artificial neural network developed in a thick blanket of connections between layers, much like the large number of neuronal cells that make up the brain’s gray matter. But that is where the similarities end. Neural networks structures have developed variations to encompass different processes, but none have truly followed advancements in neuroscience research. Studies have shown proof of networks being present in the white matter of the brain, as well as correlations between the gray matter and white matter transmissions. A revolutionary breakthrough in the field of neuroscience indeed.

The question remains: how can this information, in turn, revolutionize artificial intelligence and improve our ability to replicate human thought and logic? The next step I believe in advancing our capabilities with artificial intelligence is to truly build an entire brain for the AI models. My theory is that there is the same input layer with the features selected for the model to process. Now we need to create the brain. First, creating several hidden layers equal to the total combination of features that the team feels could accurately affect the result of the model. This would give a more comprehensive understanding of features and their effect on one another. For example, everyone is familiar with the Titanic dataset and the historical statements of, “Women and children first.” However, would a family be given access together, and how would that affect the result if the AI was able to understand that maybe a mother, child and father could be allowed passage on a lifeboat? Or, devil’s advocate, a family of five members, including young adult males would be split up due to lack of room.

The consistent issue remains, even with the current advancements in the development and performance of Artificial Intelligence. The systems still have very real, very restrictive limitations to their performance. They still fall short of the goal of replicating the design of the human brain, as well as limitations of functionality remaining in what we justify as an acceptable error. When truly we have only really created a small portion of what the human brain consists of, leaving out the portion that truly makes us differ from other creatures. This birthed the question of how a logic center, such as our “white” matter, could be created in regard to AI and current neural networks. The creation of this research paper began initially as a theory and gradually evolved into proven concepts and functional working code. The resulting novel technique has given AI a new and improved logical understanding of data and their relationships to one another. An advancement that could even be further developed into new algorithms, and advancements in how we view AI development in the future.

# **Current Systems and New Theology**

The ability to logically understand and see more complex patterns could be something that results from us taking a much deeper look at the brain and, in turn, developing a more complete artificial neural network. So, to accomplish this task, we would want to create multiple types of neural pathways. Each serves a different purpose, very much just like their biological counterparts. The first portion of the AI brain would be the architecture of the neural network selected for the task at hand. For example, in classification or regression tasks, an Artificial Neural Network (ANN) the input layer, hidden layers, and output layer make up the gray matter of the AI brain. The second layer of the AI brain would be neural pathways transporting data from each node to a Logic Band layer attached to the neural network. This would make up the artificial neural network’s logic center such as white matter does in the human brain. Let me break this down in comparison to our current methods.

Current Mechanisms of weights and biases that take the strength of connections between neurons (weights), and the biases applied at each neuron are adjusted during training to minimize the error between predicted and actual outcomes, along with the activation functions that introduce non-linearity into the model and allow the network to learn complex relationships. What I am proposing, in theory, is a band mechanic layer that tracks the flow of input through each hidden layer, evaluating the combinations of weights and their effectiveness in achieving the expected results. This band would continuously assess the accuracy of predictions refining the model’s logic by emphasizing more accurate combinations of weights and suppressing less effective ones to achieve better accuracy and understanding of more complex relationships between features.

This mechanism allows for improved outcomes in big data, complex data with large numbers of different feature inputs, and noisy data. The Logic Band will excel the greater the complexity of the data and the more epochs the model is performing allowing it to learn quickly as it progresses through the epochs, in using a toy dataset involving college students and their grades. The Logic Band Enhanced Artificial Neural Network has shown consistently better scores when compared to standard Artificial Neural Network regression tasks. The outcomes of the dataset show promise; however, big, noisy, complex data is where this method will be most beneficial. This scenario was involved a data set with under six thousand rows, and when refined to six or seven columns, it still showed better performance than the standard ANN; these were far suboptimal parameters for the Logic Band to perform within but was still able to provide a superiorly accurate output. However, this shows that the Logic Band does improve outcomes when attached to current neural networks. Exciting results on a raw dataset.

# **General Architecture and Design**

In the Logic Band framework, there are two key principles, or functions of the design of the Logic Band depending on the use case. The Logic Band technique was adapted to fit multiple AI Machine Learning, and Deep Learning models. In neural networks that utilize a dense layer, such as Artificial Neural Networks and Convolutional Neural Networks, the Logic Band is attached in the dense layer phase. This provides optimal functionality with least increase to the computational cost. Now in the case of models with feed-forward functionality, such as Bert and Transformers, the Logic Band is optimized by connecting the two feed-forward layers.

The core of how the Logic Band functions relies on two principles which work on the neural network to evaluate the data for complex relationships between the features of the dataset. The following section describes the function of the logic band as it communicates with a neural network, one being a secondary weight correction mechanism which allows adaptive scaling to modify weight values. The second key function of the Logic Band is dynamic Adjustment of Logic Band Weights to continually update the Logic Band matrix as the model learns through epochs.

The Logic Band focuses more on how each individual feature combination, as it progresses through the neural network and Logic Band architecture, affects the outcome during the training of a model. This allows the Logic Band to gather, make adjustments, and learn which features have a relationship with one another and how that ultimately affects the performance of the model. The optimal conditions for the use of the Logic band do include “noisy” data, and big feature count data. The more complex and numerous the features of the dataset the better performance difference will be noted. However, with raw datasets containing between 9-12 features, which would be very sub-optimal conditions for this architecture, side by side comparison showed the Logic Band enhanced neural network performed from 0.5% to 3% better prediction results. So, it is exciting news that even in nearly worst case scenario the enhanced model consistently outperformed an identical model without the Logic Band.

## **4.1 Logic Band Weight Correction Mechanism**

The first Logic Band’s core mechanisms consist of a traditional weight matrix W augmented by a secondary weight matrix L, this uses the logic band as a weight correction mechanism. This mechanism introduces an adaptive scaling factor to the weights in a neural network, allowing the model to adjust the importance of each individual layer outputs or combination of features dynamically. The Hadamard product allows for more precise and finer capturing of relationships between features that previously were unable recognize in most models. This provides many benefits, such as handling “noisy” data by dynamically adjusting the importance of features. Feature importance in high-dimensional data by dynamically scaling each feature's importance throughout the different stages of training. Regression tasks to recognize complex relationships between input features and outcomes, resulting in higher accuracy. Finally, improved interpretability of the model’s outputs by allowing the model to focus on certain features dynamically which can lead to enhanced interpretability of the model’s predictions. The Logic Band serves as an element-wise modifier to the standard weight matrix, essentially enabling the network to "fine-tune" its weights during training based on the relative importance of the features at each layer.

Mathematically, the Logic Band mechanism can be expressed as:

*zlogic=(W⊙L)⋅ x+b (1)*

Where:

* *W* = is the weight matrix of the layer.
* *L* = is the Logic Band weight matrix, which is of the same size as W and is trained alongside the model's standard weights.
* *x* = is the input to the layer, which can be the previous layer’s output or the raw input data for the first layer.
* *⊙* = denotes the Hadamard product (element-wise multiplication), allowing the Logic Band to dynamically scale each individual weight in W by the corresponding value in L.
* *b* = represents the bias term of the layer.

The key difference in this approach is incorporating the Logic Band weight matrix L, which enables the model to dynamically adjust the importance of each input feature based on its relevance during training while still avoiding possible overfitting. This dynamic adjustment allows the network to more effectively capture complex feature interactions more effectively, particularly in datasets with noisy or subtle relationships, by emphasizing important features and down-weighting less relevant ones. As training progresses, the Logic Band learns which features should be prioritized for better model generalization.

This mechanism ensures that, instead of treating all features with equally, importance, the model can adapt to the underlying data patterns, leading to improved model performance. The learning process for the Logic Band itself is governed by the same backpropagation algorithm that is used for traditional weights, but with the added benefit that L adjusts over time based on the network’s performance.

## **4.2 Dynamic Logic Band Weight Adjustment Rule**

The secondary mechanism of the Logic Band, which provides the functionality of dynamic adjustment of Logic Band weights, will help with understanding the Logic Band as a whole by explaining how the Logic Band updates the weights themselves as they progress throughout training. The update rule introduces momentum-based learning, allowing the Logic Band to adjust its weights gradually, incorporating prior knowledge and fine-tuning the models’ understanding of feature importance based on the gradients of the loss function.

The second critical aspect of the Logic Band mechanism is the dynamic updating of the Logic Band weights L as training progresses. To ensure that the model continually adapts to the most relevant features, the weights of the Logic Band must be adjusted based on the gradients of the loss function. A momentum-based learning approach is applied to the Logic Band weights, which allows the network to retain knowledge from previous updates while also learning new adjustments that reflect the models’ current state.

The update rule for the Logic Band weight matrix L can be described as:

*L(t+1)=α⋅L(t)+β⋅∇Lℒ (2)*

Where:

* L(t) - is the Logic Band weight matrix at time step t.
* L(t+1) - is the updated Logic Band weight matrix after applying the gradient update.
* α - is the momentum term, a hyperparameter that controls how much of the previous update is retained (like traditional momentum-based updates in neural networks).
* β - is the learning rate for the Logic Band, which controls how fast the weights adjust to new information.
* ∇Lℒ - is the gradient of the loss function ℒ with respect to the Logic Band weights.

The momentum term α ensures that the Logic Band weights do not change too abruptly, allowing the network to retain knowledge from earlier in the training process. This is particularly useful in preventing the network from making unstable or overly aggressive updates based on noisy or sparse data. The learning rate β is a key factor in determining the magnitude of updates to the Logic Band. A larger learning rate results in more significant weight changes, while a smaller rate allows for more subtle adjustments. The gradient ∇Lℒ reflects the necessary adjustments to the Logic Band weights to minimize the loss, guiding the model to focus on the most critical features. This dynamic update rule ensures that the Logic Band can learn to focus on the most relevant features during training while avoiding the potential pitfalls of overfitting or underfitting the data. It enables the model to continuously refine its understanding of which input features contribute most to the final prediction, thereby improving overall model performance.

This provides functionality to allow the Logic Band architecture to improve the model’s performance by adapting to changing data patterns over time such as in Time-Series Forecasting. Reinforcement Learning is able to dynamically adjust which features are given more importance in the decision-making process through the Logic Band, improving performance in complex and noisy feedback environments. This allows for overall improvement in performance with adaptive learning in complex or noisy data where data quality may be inconsistent (sensor networks, social media data). The dynamic adjustment of Logic Band weights allows the model to continuously learn from the most important features, effectively ignoring or devaluing noisy or irrelevant data points. Handling of complex relationships in Deep Neural Networks (DNN) through dynamic adjustment helps the model fine-tune its representation of feature importance across multiple layers, which can be essential in capturing long-range dependencies in data. The momentum-based approach to adjusting Logic Band weights ensures that the updates to the Logic Band are gradual and stable, ensuring model stability during training by preventing drastic weight changes that could destabilize the model.

1. **Artificial Neural Network Implementation**

The Artificial Neural Network (ANN) consists of an input layer, hidden layers, and an output layer. The Logic Band is architecture is implemented along the length of the existing ANN architecture. The input layer neurons feed into the beginning of the Logic Band, as the model progresses each hidden layer neuron connection is fed into the Logic Band Architecture through neuron extensions much like connections between neuron types in our own human anatomy. The Logic Band receives the weighted results of each feature and each feature combination thereafter as they combine throughout the hidden layers. The Logic Band is able to compare each combination of features and dynamically adjust their weight values to represent complex relationships previously undetectable. This representation is made and the performance of the model is improved.

The architecture of the Logic Band in an Artificial Neural Network (ANN) is relatively simple in design but potentially powerful in performance. We have a traditional Artificial Neural Network and are adding a pathway that runs beneath the network connecting each input individually, and sent down into the Logic Band where its weight is examined for accuracy. Weights of initial input features are measured and carried through to benchmark the features’ accuracy. Once they combine at the first hidden layer, weights are compared, and if the weight value of the new combination results in lower performance than the original value, then the new combination is blocked and removed through a dropout function, while the original input feature continues on. If the weight of the new combination results in improved model performance, then the original input feature is blocked and removed through the dropout function, while the new combination continues on through the Logic Band.

The nodes within each hidden layer are also connected to the Logic Band individually where the new combination of features and weights are evaluated for accuracy and impact on the final output. This is to capture any new relationships between features that could have been missed. This process continues throughout all the hidden layers and combinations of features, capturing any complex relationships that the normal Artificial Neural Network could miss. This is beneficial in big data, in which there is a high number of features, and noisy datasets. These final combinations of features dynamically evaluated are then fed into a logic layer in which the Artificial Neural Network and the Logic Band feed the processed inputs for evaluation. They are evaluated with the ‘relu’ metric and the accuracy is measured by means of the appropriate metric for the type of problem. They are calculated as they pass through the function (f(x)) to the output layer.

The enhanced architecture finally delivers an output composed of a more precise comprehension of the data and feature relationships by comparing these changes between data combinations as it is carried across the Logic Band and reevaluated. This allows for the production of an output that captures complexity and depth of understanding of data that currently doesn’t fully exist within Artificial Intelligences’ Neural Networks. This formation of an artificial logic band or “white matter” for Artificial Intelligence is a novel advancement in theology and establishes a new level of development for further advancements. The Logic Band mechanism, when attached to an Artificial Neural Network (ANN), introduces adaptive scaling to weights of each input feature dynamically. Instead of relying solely on the weight matric, the Logic Band weight matrix is introduced and acts as an element-wise modifier.

The potential benefit of dynamically adjusting weights based on observed accuracy is that of the mechanism assisting the networks discovery and retainment of more complex relationships in the data that traditional methods might miss. It could adapt more flexibility to different types of data and tasks, through improving the networks’ ability to generalize from training data to unseen examples. This allows for more focus on accurate weight combinations could lead to better performance and lower error rates, particularly in complex or noisy datasets. The more complex, or larger number of features, the data the better the Logic Band is able to perform. So big data and complex feature training will yield the best performance improvement to the current artificial neural network models. While continuous evaluation and adjustment could refine the networks’ predictions, leading to more accurate outputs. This could be the new evolution of artificial neural networks, and artificial intelligence in general. Taking a step towards mimicking the structure of the human brain itself.

1. **Model Adaptation**

The design of this artificial logic band has been crafted very carefully to make sure not to add a significant amount of computational costs and time to ensure model stability during the training process. The Logic Band is a great contribution to any artificial neural network architecture and a great tool for evaluating weights and improving the performance of the models. This method could be implemented to build a logical reasoning that is more in-depth and comprehensive for any artificial neural network. The concept is novel and could open the door for further more comprehensive research into neural network architectures, while providing a comprehensive methodology in which to explore further in depth. This could lead to the development of new neural networks architectures that better capture complex relationships and research into these architectures could expand the boundaries of what is possible with the current neural networks.

The Logic Band has successfully been adapted to pair to multiple artificial neural networks such as Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Transformers, BERT, and LSTMs. Performance benchmarking against current methods have revealed not only an increase in performance of these models, proof of concept, but also confirmation of intent of the design. The last of which is exciting when looking at real world applications of such enhanced models.

In comparison to Artificial Neural Networks (ANN), the Convolutional Neural Networks’ Logic Band is applied only to the dense phase of the model to reduce the effect on computational costs, where similarly in ANNs the Logic Band is applied throughout the entirety of the model which consist of a dense layer throughout. The Logic Band enhanced CNN offers high-level feature aggregation with image recognition and object detection processes, while Logic Band enhanced ANNs are able to capture complex relationships between feature improving accuracy of the model.

The world of Artificial Intelligence (AI) is ever-evolving especially in the field of natural language processing (NLP). The Logic Band has been adapted to fit several deep learning models used for natural language processing as it allows dynamic scaling of weight importance, helping the model focus on meaningful tokens across varying contexts and the handling of contextual relationships. The Logic Band introduces adaptive learning of feature importance through fine-tuned control over input-output interactions which is especially useful for tasks like sentiment analysis, text classification, or question-answering, where not all words are equally important. Attention mechanisms already create computational strain in natural language processing models, therefore applying the Logic Band to dense layer phases, such as fully connected layers and feedforward networks, preserves efficiency without adding unnecessary computational strain to the model, allowing avoidance of computational bottlenecks and inefficient functionality of the Logic Band.

In recurrent architectures, such as Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM), maintaining the flow of meaningful information over time steps is crucial. The Logic Band can modulate the hidden-to-hidden weight connections, ensuring that important features remain influential while reducing noise. The integration of the Logic Band layers into Natural Language Processing (NLP) models adds another layer of adaptive learning, making them more effective in capturing complex relationships across tokens. The Logic Band improves the Recurrent Neural Network (RNN) through adaptive learning, which is critical for time-series tasks, forecasting, or sequence classification tasks. By dynamically scaling each time step, the network is able to focus on meaningful features throughout the sequence. This makes a Logic Band enhanced Recurrent Neural Network provide better generalization and fine-grained control over feature importance throughout the RNNs’ hidden state evolution.

In Transformer-based models, such as BERT, each token interacts with every other token through self-attention mechanisms. The dense layers in the feedforward network and output layers are ideal candidates for the Logic Band. This allows the model to learn feature importance beyond attention scores. This Transformer formulation ensures that the model adjust token importance dynamically during training, helping with tasks like entity recognition or summarization. The use of the Logic Band from the inputs’ feedforward network to the outputs’ feedforward network will emphasize relationships between encoder and decoder features but does not directly adjust the decoders feedforward network based on its own outputs. This provides a simpler architecture with fewer parameters and reduced computational overhead, focusing on improving transformation of encoder outputs into meaningful decoder inputs, enhancing cross-feature relationships. This method reduces the risk of overfitting due to fewer trainable parameters, and makes the model easier to train and debug. However, it provides limited adaptability, in such cases as , language generation or summarization that requires independent logic refinement in the decoders’ feedforward network.

The use of the Logic Band from the inputs’ feedforward network to the outputs’ feedforward network, and a second Logic Band from the outputs’ feedforward network to the inputs’ feedforward network allows each Logic Band to specialize in different types of relationships. It allows the first Logic Band to gather encoder-to-decoder relationships, and the second Logic Band to refine the input context dynamically through feedback from decoder to encoder. This can be incredibly beneficial in improving performance on tasks requiring fine-grained bidirectional understanding such as translating languages and question answering. It would also provide enhanced handling of complex datasets where token relationships evolve dynamically. This all does come at the cost of more parameters and operations, especially in high-dimensional data, computational costs may need to be monitored. It would increase the training complexity where careful management is necessary to avoid overfitting and potentially vanishing or exploding gradients.

Both methods have their strengths and use case scenarios. A single logic band would be preferred where the dataset is relatively simple or the task involves straightforward transformations, such as translation where input and output have a direct relationship. The double logic band is suitable for tasks requiring deeper contextual understanding or feedback between input and output such as summarization, question answering, multi-hop reasoning. This is more suitable for larger datasets that are complex where additional parameters can improve feature interaction modeling without overfitting.

1. **Summation**

In conclusion, this may be the next step in the advancement of Artificial Intelligence and the next step in making it closer to mimicking the human brain itself. This began as a great theory founded in human neuroscience, that closes in on the goal of artificial intelligence, which is to replicate the human brain and its function as closely as possible. That theory developed into code and mathematics to back the theory, followed by proof of concept through working with datasets. The science and healthcare experience gained through a paramedic career merged with newly developed data science career path led to the conception of this novel architecture. This is a complex reasoning of relationships in data that has successfully improved outcome accuracies and model performance. This may just be the first step into developing a huma-like logical understanding of data for Artificial Intelligence. The final piece of the puzzle in accomplishing a replica of the human brain, the Logic Band is the counter part to the current neural network systems and through further development will increase the capabilities of AI as we know it.

Currently, development of another Logic Band architecture is already underway, with it the AI models will be able to autonomously perform feature selection in which complex relationships discovered will become new features to be evaluated and sub-optimal performing features will be removed to allow for optimal data comprehension starting from a raw dataset. The further development of this theology is an exciting advancement for artificial intelligence and the beginning foundation for the complete development of the “white matter” component of the artificial intelligence brain. Development of different Logic Band structures such as there are numerous neural network architectures offers countless possibilities. The dynamically adjustable weight system allows for more complex relationships to be discovered in data is exciting. The applications are nearly endless: better weather forecasting, stock predicting, marketing insights, drug discovery, autonomous driving cars, even improvements to artificial intelligence assistants. The improvement of current AI applications in real world applications are nearly endless as we are in an era where AI is so vastly integrated into our everyday lives.